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Research Article

Visibility Analysis with the Multiscale Implicit TIN

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Abstract
Visibility analysis is now a key function of many geographical information systems. It is also one of the most contentious tools, as it is notoriously prone to error. The paper will demonstrate the versatility of the *Multiscale Implicit Triangulated Irregular Network* (TIN) for the application of intervisibility analysis at multiple resolutions. This approach allows for the integration of three-dimensional (3D) topographic features with the terrain surface. The multiscale TINs are derived from generalising digital contours at a variety of lateral tolerances. The models' performances are evaluated from an extensive field study undertaken in the South Wales valleys. Results suggest that the accuracy of intervisibility analysis is very dependent upon the availability of good quality 3D topographic data. In our study, such data were shown to improve visibility performance by more than 44% over its *bare-earth* TIN equivalent. Interestingly, generalisation of the TINs had very little effect on visibility performance. In addition, a Monte Carlo approach to sensitivity analysis was found to be detrimental to the accuracy of visibility prediction in the full terrain and topographic models. However, this probable approach can improve intervisibility performance by up to 18% on a *bare-earth* TIN. The range of these visibility modelling scenarios demonstrate the flexibility of the *Multiscale Implicit TIN* for digital surface modelling.

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1 Introduction

Intervisibility and viewshed analysis are amongst the most common functions of those GIS that support digital terrain modelling. In the main, they are used to aid planning decisions, such as the siting of contentious developments with the aim of minimising visual intrusion, or alternatively for identifying locations which maximise the field-of-view, such as for broadcast coverages, scenic viewpoints, watchtowers, or missile defences (Franklin and Ray 1994). Such functions require the computation of visibility for the surface itself or for objects located on the surface. The problem is essentially a query problem (De Floriani and Magillo 1999), whilst the key to solving such problems is the availability of flexible modelling strategies for the representation of the surface itself, preferably at multiple scales, and for the objects on that surface. It is now well documented that small elevation errors can propagate through to large application errors, particularly for intervisibility and viewshed analysis (Fisher 1991, Huss and Pumar 1997). At the same time, it is rather worrying that the commercial software available to query the surface on issues of visibility are often invalid and contradictory (Fisher 1993). This is due to a number of factors, including elevation errors in the digital terrain model (DTM); the inaccuracy and misrepresentation of the surface features; interpolation errors; the choice and resolution of the DTM; and poor intervisibility algorithms. These problems are compounded by a reluctance to validate the performance of DTMs and topographic models for visibility analysis with actual field trials. Validation is often impractical and costly, but ignorance of the magnitude of errors within visibility analysis results in further misuse of the GIS, often for critical decisions. Recent studies have attempted to show and report the sensitivity of intervisibility functions to small database error, but GIS developers have been slow to take on board these tools, preferring to classify and visualise intervisibility as a definitive Boolean variable of visible or not visible, rather than possibly visible or probably visible. Such deterministic reasoning in visibility algorithms leaves no room for error, particularly at a time when the majority of users now accept that digital terrain model error is inevitable.

Kidner et al. (2000) present a data storage and access scheme for generating triangulated terrain models that adapt their content and level of detail to the requirements of the user. Furthermore, this *Multiscale Implicit TIN* allows for the integration of the topographic features as a fully-fledged digital surface model (DSM) or just the terrain itself as a digital terrain model (DTM). The *Multiscale Implicit TIN* offers users a fitness-for-use solution to the problem in hand (Kidner et al. 2000). As such, it is not constrained to a single scale representation of a terrain or its surface features, but acknowledges that user queries are invariably unique, hypothetical and exploratory in nature. A range of modelling strategies is often best suited for these queries, for example, at small scale or large scale and with or without topographic surface features. The founding principle of the *Multiscale Implicit TIN* is that the data structure should be derived at run-time by the requirements of the user and the specific queries asked of the system. Kidner et al. (2000) give an introduction to terrain modelling with multiscale TINs and the background to the development of the *Implicit TIN*. Essentially, the *Implicit TIN* differs from a conventional TIN in that only the vertices are explicitly stored, together with the definition of any linear constraints. No topological relationships defining the triangulation are recorded. TIN topology is reconstructed by a triangulation procedure if and when it is required for a user operation. The triangulation procedure can itself be thought of as being an integral component of the *Implicit TIN*. In the past, similar models have been limited to terrain visualisation at multiple scales, with little application to traditional GIS analysis.

The aim of this paper is to assess the flexibility and accuracy of the *Multiscale Implicit TIN* for a range of intervisibility queries. In particular, the value of 3D topographic features and the effect of database generalisation are analysed. Section 2 introduces the problem of intervisibility analysis, while Section 3 discusses the issues relating to visibility on triangulated irregular networks. Section 4 presents an overview of the consideration of error in digital terrain modelling and discusses approaches for modelling *probable* visibility based on an understanding of the likelihood of elevation errors in the source data. Section 5 describes the field study undertaken to validate the *Multiscale Implicit TIN* model for an intervisibility assessment and presents the results with and without topographic features at multiple resolutions. Section 6 takes this study further by examining measures of *probable* visibility. Section 7 concludes with the findings of the study and some recommendations for the way forward.

2 Intervisibility Analysis

Intervisibility analysis simply relates to the classification of whether two locations on a surface are line-of-sight (LOS) or non line-of-sight (NLOS). This is often extended by considering the visible area, or viewshed of an observer location. This is a common GIS function, which has come under close scrutiny in recent years (Fisher 1993, Huss and Pumar 1997). Intervisibility is determined by first retrieving the cross-sectional terrain profile, or stepping through the DTM and associated topographic databases or digital surface model (DSM), and identifying any possible obstructions between the observer and target locations. As each elevation is interpolated from the DTM or DSM, the angle subtended from it to the observer (α) is checked against the angle subtended to the observer from the target (θ). If the surface extends above the line joining the observer and target (i.e. $\alpha > \theta$), then the profile is classified as NLOS. If no such surface extrusions intersect this line, then the observer and target are intervisible or LOS (Figure 1).

Conceptually, the determination of intervisibility between two locations is simple. However, current implementations within GIS have profound shortcomings in their ability to yield useful and generalisable answers to simple queries related to the viewable area (Fisher 1996a). For example, the viewshed of an observer is not necessarily the same as the area that can view the observer's location, as a distinction needs to be made between the ground and viewing heights. Similarly, tools are fairly limited for quantifying the degree of visibility of a surface object. For example, in visual impact assessment, a distinction needs to be drawn between whether an object is fully

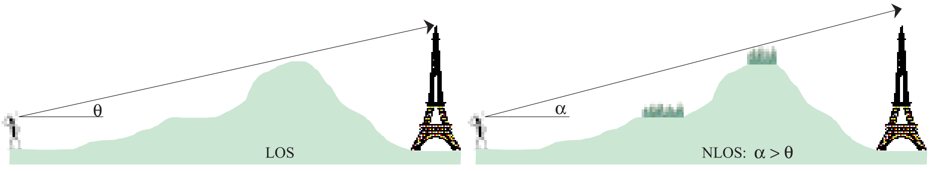


Figure 1 Determination of whether a surface profile is line-of-sight (LOS) or non line-of-sight (NLOS)

or partially visible, e.g. a 65 metre high wind turbine, or just the tip of its blades (Dorey et al. 1999). These refinements to the traditional LOS algorithm may detract from the key issue of the accuracy and validity of today's commercial GIS solutions. Fisher (1993) identifies alarming discrepancies between the calculated viewshed of a variety of packages for the same input DTM and observer locations. There is clearly a lack of understanding in the implementation of intervisibility algorithms by the GIS vendors. This relates to the specification of what constitutes the *view* to be determined (i.e. the observer to target line); how these are specified in local DTM coordinates; and how elevations are retrieved or interpolated from the DTM.

Whilst these conceptual errors will generate large application errors, they are greatly compounded by database errors, i.e. inaccurate DTMs and DSMs. The DTM debate of regular grid DEM versus triangulated irregular network (TIN) has raged for the last 25 years without a clear winner, due mainly to the limitations of independent data sources for direct comparisons (Kidner et al. 2000). For this research, we are confining the discussion to the use of the TIN, as it offers greater flexibility, and allows for the integration of topographic features without compromising or generalising the data resolution. Furthermore, we are limiting the visibility problem to the simplest case scenario, i.e. the intervisibility between two known locations. This is not only the easiest to verify in the field, but also the most crucial of all the different visibility queries that can now be asked of a GIS. For a full review of viewshed variants, the reader is referred to the work of Fisher (1996a, b).

3 Intervisibility on TINs

Determining intervisibility on a TIN is not as straightforward as performing the same task on a regular grid DEM. The TIN requires more complex algorithms to manipulate the explicitly defined topology (Theobald 1989) and more sophisticated and specialised data structures to encode the visibility on a terrain (De Floriani and Magillo 1999). This is particularly true for the more advanced and diverse range of visibility-related problems now being asked of GIS, such as for a moving observer, or for determining optimal solutions for minimising or maximising visibility. The simplest task is to calculate the intervisibility between an observer and target location, as in Figure 1. The biggest difference between using a regular grid DEM and a TIN is the sampling strategy for interpolating elevations along the profile cross-section. With a DEM, the sampling strategy can be regular (e.g. every 10 metres) or semi-regular (e.g. at every row and column intersection of the grid). In general, a regular stepping algorithm combined with a bicubic (or higher) interpolation algorithm is advisable, as this will identify the variation within the grid cell. For a TIN, the majority of systems still use linear interpolation. For the most part this is perfectly acceptable, particularly if linear interpolation is used as part of the TIN construction algorithm, such as within an error-constrained Delaunay pyramid. A variety of higher-order interpolation algorithms have been devised for the TIN to ensure that the interpolated surface has continuous first derivatives (Hutchinson and Gallant 1999). These include the bivariate interpolation methods of Akima (1978) and Clough and Tocher (1965). However, for most visibility functions, the computational demands of higher order interpolation algorithms preclude their widespread use. As such, linear interpolation across the triangle edges is the favoured approach for most intervisibility algorithms.

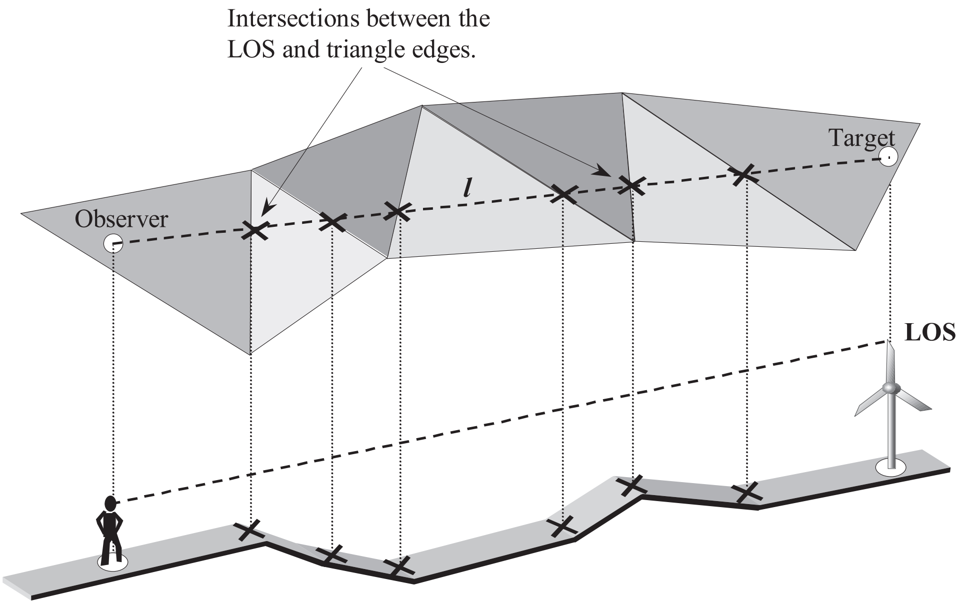


Figure 2 Re-construction of a surface profile (*l*) through a TIN with linear interpolation across the triangle edges

A TIN LOS algorithm initially requires that the triangles enclosing both the observer and target locations are identified. This is necessary in order to interpolate the elevations at these points before determining the angle (θ) between them. Calculating the intervisibility of the points then proceeds by the identification of the intersections between the projection on the x–y plane of the straight line segment joining the observer to the target, and the edges of the TIN (De Floriani et al. 1994). The process of interpolating a terrain profile along a line *l* between the observer and target, through a TIN is illustrated in Figure 2. The profile consists of a continuous series of straight-line segments, each of which is defined by the locations of two consecutive intersections between *l* and the TIN surface. The intervisibility of two points can be ascertained by comparing the elevation of the surface profile at each edge intersection with its corresponding height on line *l*. Alternatively, and more simply, the angle subtended to the observer at each edge intersection (α) is compared with the angle subtended from the target to the observer (θ). With the *Multiscale Implicit TIN*, the topology of the TIN is unknown before the intervisibility query is specified. As such, only the triangle edges that intersect the line *l* need to be retrieved, together with the triangles of the observer and target locations. Kidner et al. (2000) illustrate the methodology at multiple scales.

The LOS intervisibility algorithm can be extended to determine the viewshed of the observer by performing multiple tests to all possible targets within the TIN. The target locations on the TIN are more usually defined as the triangles themselves, or occasionally the edges or vertices. For example, the TIN viewshed algorithms of Lee (1991) and Goodchild and Lee (1989) attempt to define visible triangles. In both cases, however, the resulting viewshed is not a precise viewshed in the context of the TIN surface, but rather a generalisation of it. This is because the algorithms make no attempt to split individual triangle facets into visible and non-visible portions. A triangle is deemed visible if and only if each of its three edges are fully visible. De Floriani et al. (1994) avoid this criticism by treating the TIN as a continuous surface, which in effect ignores the constraints of the underlying triangular structure. Areas that are visible from the observer viewpoint are determined precisely by sub-dividing triangles, even though it will generally produce a fragmented set of slivery triangles. The general problem is synonymous with the hidden surface removal problem for a 3-D scene, in which the portions visible from the observer are projected onto the image plane (De Floriani and Magillo 1999). As the aim of this study is to validate the intervisibility along recorded profiles, the TIN viewshed algorithms are unnecessarily complex and computationally demanding for such a small aspect of the general problem. The algorithm used in this study is based on the approach illustrated in Figure 2, but adapted for the *Multiscale Implicit TIN* as in Kidner et al. (2000).

4 Error and Probable Visibility Modelling

GIS has been adopted by individuals and agencies who see its benefits in terms that often include increased accuracy compared to previous methods, yet the data stored in GIS are in most cases no more accurate. The GIS user needs to have an awareness of the problems associated with digital spatial data and an understanding that any GIS application is only as good as the data it deals with (Giordano et al. 1994). Unfortunately, the issue of data quality is frequently overlooked in GIS, or rather the quality of GIS products are often incorrectly judged by the visual appearance of the end-product on the computer screen, plotter or video device (Burrough and McDonnell 1998). Even after twenty-five years of GIS development there is still inadequate attention paid to the study of how errors arise and propagate through the GIS system (Burrough and McDonnell 1998). If it is accepted that the data on which GIS analyses and reasoning are based are not perfect, then perhaps greater emphasis should be placed on showing a measure of *likely* error. This would enable the user to make the final judgement as to the suitability of the data and decide its *fitness-for-use* for the analysis in question.

Error in digital terrain models is widely acknowledged, and has been the subject of some study, which has concentrated on the nature and description of the error, rather than its propagation into derivative products. Error, in terms of terrain modelling, usually relates to the incorrect elevation being recorded at a given location. The sources of error are many and varied. A significant factor affecting the accuracy of a DTM is the method used to gather the original source data. However, even when the original survey generates relatively accurate data, the GIS user often feels obliged to degrade it by converting the data into a more convenient format, such as a regular grid digital elevation model, without ever considering the likelihood of the error introduced. For example, consider the Ordnance Survey regular grid digital elevation models. The original field surveys that form the basis of this data were collected primarily more than fifty years ago which is when the corresponding contours were derived and drawn. Subsequently, the contours were digitised, triangulated, and interpolated onto a regular grid. At each stage of the process, error is introduced and propagated into the model.

Carter (1989) examined a number of US Geological Survey (USGS) DTMs in an attempt to locate and categorise any errors found. He defines two categories of error, *relative* and *global* error. Global errors are found in situations where the general form of the land surface is adequately defined by the digital data, but the total model departs significantly from the source map or the actual land surface. In contrast, relative errors refer generally to single elevation values being inconsistent with their neighbours. These categories broadly correspond to those suggested by Caruso (1987), which are also used by the USGS. Caruso categorises error into three main classes, *systematic*, *random* and *blunders*. Blunders are those types of major errors that exceed reasonable limits, and are expected to be identified and removed from DTMs when they are edited prior to release. Systematic errors may be due to the nature of data collection, whilst random errors are the most difficult to remedy, since they are difficult to identify.

However DTMs are generated, the recorded values will incorporate some degree of error (measurement error, interpolation error, etc.). The root mean square error (RMSE) is the measure most frequently used to record accuracy, both in experimental and in theoretical analysis of DTM accuracy (Li 1988). It is also the standard measure of error used by surveyors around the world (Fisher 1998). It is based on the formula:

$$RMSE = \sqrt{\frac{\sum z - w^2}{n}} \tag{1}$$

where z is the recorded elevation in the DTM, w is the elevation measured in a check survey, usually at a larger scale, and n is the number of locations tested.

In reporting just the RMSE, the assumption must be made that the error contained in the DTM product is unskewed and normally distributed around a mean of zero. In the UK, the OS adopts the approach of reporting error as a single nationwide RMSE value. For example, in the accompanying documentation for the OS 50 metre DEM product, it is reported that whilst each tile is not individually checked for its respective degree of error, those that have been tested have a RMSE of between two and three metres. Likewise, for the OS 1:10,000 scale contour data, in areas with a 5m vertical interval, the accuracy of the contours is reported as being in the order of $\pm$ 1.0m RMSE. For areas with a 10m vertical interval, the RMSE increases to approximately $\pm$ 1.8m (Ordnance Survey 1999). The geographical extent of the OS check surveys and the range of terrain types are unclear in the OS documentation. Therefore the user can only assume, rightly or wrongly, that this degree of error is homogeneous across the entire country, from the steepest mountain to the flattest coastline (Fisher 1998).

If it is acknowledged that error exists in a DTM, then it follows that error will also be present in the outcome of any analysis performed on it. It is important to establish whether or not that error is such that the possibility of an erroneous outcome is significant enough to invalidate the results. If it is, then the DTM is not *fit for use* for the application concerned. Answering this question is difficult in many forms of GIS analyses because the results are often given as Boolean values, i.e. true or false. An alternative may be to predict the probability of the results being correct, given the error contained in the DTM (Fisher 1995). One approach is to use a Monte Carlo simulation technique to model the error contained in the DTM and produce alternative error-constrained versions of the surface. The particular analysis is then performed on each instance of the DTM, thereby giving a set of multiple versions of the outcome. Using this method, a level of confidence can be obtained in the results given. A disadvantage of this method, however, is that high accuracies are reached only when the number of runs is sufficiently large, which may cause the method to become extremely time consuming (Heuvelink 1999).

The data quality statement for many DTMs requires no more than the RMSE to be reported (Fisher 1998). Using this simple description of error, it can only be inferred that error at a particular location occurs independently of any other point in the immediate vicinity. This corresponds to the *relative* error described by Carter (1989). Assuming this to be the case, an error model may be generated by drawing random values from a normal distribution, with mean equal to 0, and a standard deviation equivalent to the reported RMSE. The mean of these error values (the bias) shows the systematic error across the dataset, whilst the standard deviation of the errors (equivalent to the RMSE) shows the dispersion of the errors. Adding the error values to the elevations of the DTM gives an instance of the DTM that has the essential qualities of both the original and the error that is known to occur in it. Furthermore, because the DTM is known to be in error by the amount reported, it could be argued that such a derived DTM is actually more realistic than the original (Fisher 1998). The process, described by Fisher (1991), can be summarised as:

(1) Define a standard deviation of a normal distribution (S = RMSE)
(2) Read Original_Elevation for the current cell or vertex
    (a) Generate a random number from the normal distribution with mean = 0 and standard deviation = S;
    (b) Add the random number to the Original_Elevation for the current cell, to give the New_Elevation;
(3) Repeat step (2) for all DTM vertices

In effect, this results in the generation of an error model consisting of random white noise, where each value is totally independent to those of its neighbours. Consequently the DTM becomes perturbed (in proportion to the value of the RMSE), and may resemble little of what we know about the smoothness of real terrain, or indeed a typical DTM. This is because the surface of the error model has no spatial autocorrelation. In contrast, a surface with high spatial autocorrelation will appear far smoother. Goodchild (1987) defines spatial autocorrelation, in its most general sense, as the degree to which objects or activities at some place on the Earth's surface are similar to other objects or activities located nearby and reflects Tobler's first law of geography that "everything is related to everything else, but near things are more related than distant things". Although the distribution of error across the area of a DTM is currently unknown, and the factors that may affect the distribution of error are largely unresearched, Fisher (1991) argues that rather than the error present in a DTM being random, it will *probably* have a high level of spatial autocorrelation. That is, if one point is in error, then its neighbouring points will also be in error to a similar degree. To model the occurrence of spatially autocorrelated error, an algorithm such as Goodchild's (1980) which measures autocorrelation by means of Moran's (1950) I index could be used. Moran's I index has been used in almost all studies employing spatial autocorrelation (Upton and Fingleton 1985). The I values range from $+1$ meaning strong positive spatial autocorrelation, to 0 meaning a random pattern, to -1 indicating strong negative spatial autocorrelation. An adaptation of the algorithm proposed by Goodchild (1980) for generating error models on DTMs, is presented by Fisher (1991):

(1) Define a target autocorrelation (I_t) and a standard deviation of a normal distribution (S = RMSE);
(2) For each DTM vertex, generate a random value with a normal distribution of mean = 0 and standard deviation = S;
(3) Calculate the spatial autocorrelation of the error field (I_1);
(4) Randomly identify two vertices in the DTM;
    (a) Swap the values of the two vertices;
    (b) Calculate the new spatial autocorrelation (I_2);
    (c) IF $I_t > I_1$ and $I_2 > I_1$ THEN retain the swap, and $I_1 = I_2$
    OR IF $I_t < I_1$ AND $I_2 < I$ THEN retain the swap, and $I_1 = I_2$
    ELSE Swap the two vertices back to their original values;
(5) Repeat step (4) until ($I_t - I_1$) is within some threshold.
(6) For each original DTM vertex, add the value in the corresponding autocorrelated field.

Fisher (1991) used both of these approaches to model error in regular grid DEMs in order to identify the *probable viewshed*. Initially this binary or Boolean viewshed on the error-constrained DEM is found. By repeating the process n times, the average of the binary viewsheds produce the probability of a target location actually being visible (Figure 3). In the resulting probable viewshed, a location with a value equal to 1 is definitely within the viewshed, and those areas with progressively lower values are proportionally less likely to be visible. If a location has a value of 0 then it is entirely outside of the viewshed having never occurred in any of the binary viewsheds.

More recently, Fisher (1998) applied a more localised error model to DTM elevations based upon discrepancies between spot heights and a 50m (1:50,000 scale) DEM. The error model is then adjusted until the specified level of spatial autocorrelation is achieved via the swapping of error vertices. In this manner, the structure of the error field is controlled around locations of known degrees of error.

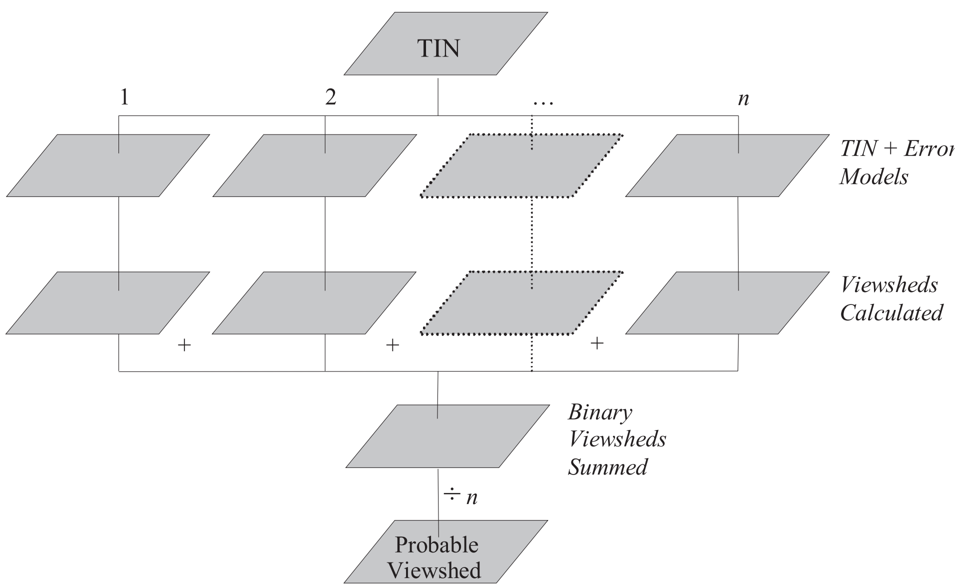


Figure 3 Creation of the probable viewshed (after Fisher 1995)

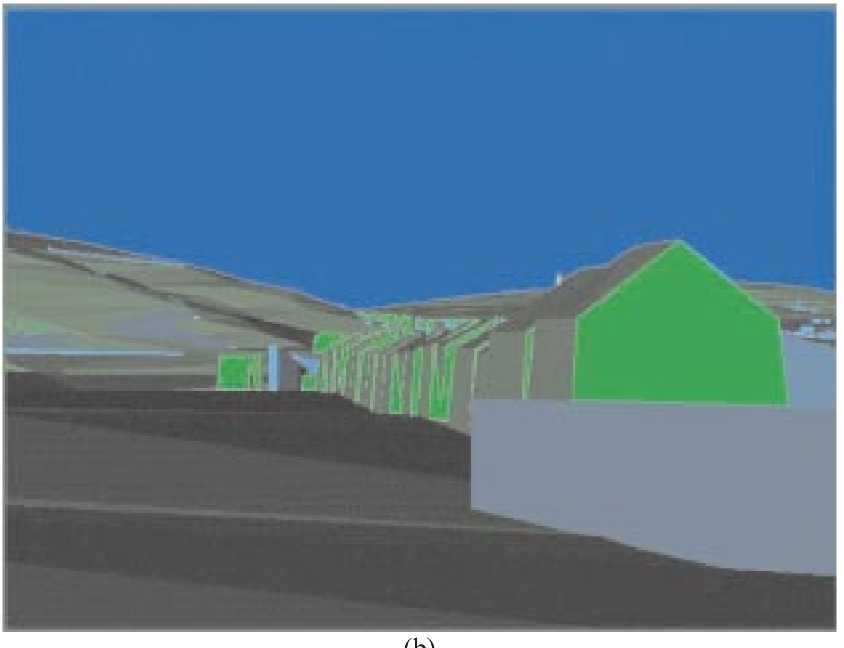
Additionally, the normal curve from which the random values for the error field are generated is defined with respect to the standard deviation and mean, calculated using the interpolation errors. Fisher observes that in the case of the OS DEM, both the mean and the standard deviation were significantly higher than those reported by the OS. However, it must be recognised that in using such a basic DEM representation, any comparisons between values interpolated from the DEM and those of the spot heights are likely to result in unnecessarily large differences. Since these errors form an important part in the methodology, care should be taken to ensure that an appropriate interpolation algorithm is used.

5 Field Study and Visibility Results

To evaluate the performance of GIS solutions for visibility analysis it is necessary to compare model predictions with line-of-sight (LOS) observations taken in the field. Tindal and Garrad (1993) comment that "validation plays an important part of predictive tools in all engineering applications". GIS contain many predictive tools, yet the need for validation has largely been ignored by the GIS community. Fisher (1993) argues that "the viewshed is not actually verifiable in the field nor can it be logically validated, anything more than trivially". As the viewshed is defined as the complete visible area of a viewing location (or the complete area from which an object is visible), a complete verification is perhaps impossible. However, by breaking down the viewshed into individual transects and examining a subset of these, a non-trivial approximation of viewshed accuracy is possible. In order to attempt this, 365 viewing locations were surveyed using a differential GPS for an area centred around the Taff Ely wind farm near Gilfach Goch in South Wales (Kidner 1997). Three OS trig pillars were used to initialise the base GPS receiver in order to define a local base station of known coordinates in close proximity (i.e. no more than 3 km) to the viewing locations that were surveyed. Tests at local OS benchmarks within the study area suggested a very high correlation with the GPS-surveyed elevations. These were all within a vertical tolerance of 10 cm. Whilst these tests cannot be taken as a measure of the overall accuracy of the GPS surveying against the actual terrain (since the OS ground control points were used to initialise and test the GPS), we can conclude that there is a very strong correlation between the GPS coordinates and the OS ground control, i.e. there is confidence in the quality of the surveying undertaken. As the OS ground control points were used by the OS to survey and derive the digital contour lines, it follows that differences between the GPS surveyed elevations and the interpolated heights from the digital contour data can be used as a measure of elevation error in the contour data with respect to the ground control elevations. Some observers have expressed concern in the quality of the OS ground control. This is beyond the means of most people and certainly ourselves to verify. However, for our field study this is irrelevant, as both the *Implicit TIN* and the surveyed observer locations use the same ground control or datum. Any errors in the OS trig pillar elevations will be relative, as they will be inherent in both our computer model and our "real world" model.

For each of these surveyed viewing locations, the visibility of an anemometer (35.5 m in height) on a local wind farm was recorded, along with a digital photograph of the view, primarily for identifying any discrepancies in the digital terrain model and its surface objects (Figure 4). The majority of observer locations were within the local

(a)



(b)

Figure 4 (a) Actual view to anemometer mast (b) VRML representation of the Implicit TIN model of this scene with buildings and roof structures (allowing the mast to be correctly classified as being "line-of-sight"). The mast is visible above the roof of the second house in the foreground

Table 1 Correlation between observed and calculated visibility of 365 path profiles for a variety of Implicit TIN representations at multiple tolerances

Multiscale	Bare TIN	TIN with Buildings	TIN with Vegetation	TIN with buildings and Vegetation
0m Tolerance	48.26%	80.56%	65.87%	92.86%
2m Tolerance	47.88%	80.56%	65.87%	92.86%
5m Tolerance	47.49%	79.76%	65.48%	92.06%

village communities, whilst the terrain itself was quite hilly (see Sparkes 2000 for a more detailed overview). Kidner et al. (2000) give a description of the approach for integrating topographic features into the TIN as a digital surface model (DSM).

The visibility of the anemometer was checked against a number of *Implicit TIN* representations of the same landscape. The objective of this was to identify the significance of different parameters within the *Implicit TIN* model and also the effect of generalisation or different error tolerances on visibility performance. Multiscale versions of the Implicit TIN were generated by defining contours with *the Line Generalisation (LG) tree* (Kidner et al. 2000). Very few studies have been undertaken to examine the performance of generalised DTMs. Of these, Fisher (1996a) examines the effect of changing the resolution of a regular grid DEM on viewshed performance, with variable results.

Table 1 presents a summary of the correlation between observed and calculated visibility for three multiscale TINs with LG-Tree tolerances of 0m, 2m, and 5m. The first of the three models represents a TIN in which every single vertex of the original 1:10,000 scale OS (Landform Profile) Contour DTM is fully maintained. The other two models allow a lateral error of up to 2 metres and 5 metres in the original contour lines.

The first column of Table 1 represents the number of correct interpretations made from multiscale "bare-earth" TINs with no topographic surface features modelled. In effect, the line-of-sight is more likely to be wrong than right if no surface features are represented. The second column reports the improvement in these TINs' performances when the buildings on the landscape are inserted into the models. The third column reports the improvement in the TINs when just the trees and other vegetation such as hedgerows are inserted into the model. Finally, the fourth column represents the performance of the TINs when all the available surface features are inserted into the models.

The results are quite surprising for a number of reasons. Firstly, there is no significant degradation in the performance of the multiscale TINs with the constrained (lateral) error tolerances. At the outset of the research, a decision was made to preserve all the original data within the *Implicit TIN*, on the basis that if the data was acquired at such fine resolutions then it should all be directly honoured and not "thrown away". However, these results have changed our attitude towards the validity of this philosophy. There is obviously over-sampling along the source contours, but the effect of contour line generalisation has never really been studied with respect to its propagated effects on other derivative products, such as visibility. For example, line generalisation has been advocated as a means of reducing the problem of flat regions in TINs. Whilst it may work to some extent, it cannot guarantee a consistent TIN and has been largely dismissed for a variety of reasons (Ware 1998). These results suggest that generalisation is valid within reason. In our models, generalisation beyond a 5 m tolerance leads to the crossing of contour lines. Whilst these instances can be automatically identified and remedied, it was not thought worthwhile to generalise past the 5 m tolerance level, as the benefits are largely accrued once the user first accepts the principle of multiscale generalisation. For example, the 2m tolerance reduces the number of TIN vertices by 71%, whilst the 5m tolerance reduces the number of vertices by 84%. These reductions are similarly reflected in the computational requirements of the TINs.

Secondly, the results demonstrate the requirement for good quality 3D topographic data for visibility analysis. The vast majority of papers that have addressed the subject of visibility analysis over the last 30 years quite often fail to take account of topographic features within the line-of-sight or viewshed calculations. Perhaps this has been largely due to the cost of 3D topographic data in the past, but this unwillingness to broach the subject has propagated through to ignorance of the issues when it matters most. For example, many of today's visual impact assessments undertaken as part of an environmental impact assessment fail to take account of the effect of topographic features on the resulting viewsheds or zones of visual influence. This is often to the detriment of the developer submitting the planning proposals, as topographic features can only act as a screen to visibility, thereby reducing the visual impact of contentious developments.

Thirdly, the full results (Sparkes 2000) give us a good understanding of the quality of the source digital terrain data. Whilst it is very easy to bemoan the quality of our national mapping agencies' digital products, particularly for terrain, the results of Table 1 suggest that there is no substitute for good quality 3D topographic feature and height data. Only 7% of profiles were mis-classified, due to a combination of elevation error in the digital contour data and the mis-representation of some of the topographic features and their heights. Sparkes (2000) gives a fuller description of some of the erroneous profiles. As such, we can conclude that datasets such as the OS 1:10,000 scale (Landform Profile) contour data are suitable for visibility analysis and other similar applications such as radiocommunications planning, provided topographic features are incorporated. If not, then the likelihood is that the application will be wrong more often than it is right.

6 Probable Visibility Results

As already discussed, where a global RMSE error measure is provided by the data supplier, it may be desirable to estimate error more specifically for the given DTM. This can be achieved by using spot heights of a higher accuracy than the original survey, to determine the RMSE and mean of the error. As part of this study almost one thousand accurate terrain point measurements were obtained. These consisted of the 365 observer locations measured using a differential GPS, and others from a manual survey using traditional techniques based on electronic theodolites. The elevations of each were compared with linearly interpolated heights from the Implicit TIN of OS 1:10,000 scale contours.

From this error information, it is possible to generate improved location-specific error statistics. The results of this experiment show that on average, the error has a small negative bias and a RMSE of approximately 1.6 m. For this particular area, both error values are relatively close to those implied by the OS. In addition to the statistical measure of error, it is also possible to view the error present at specific geographical locations (Figure 5).

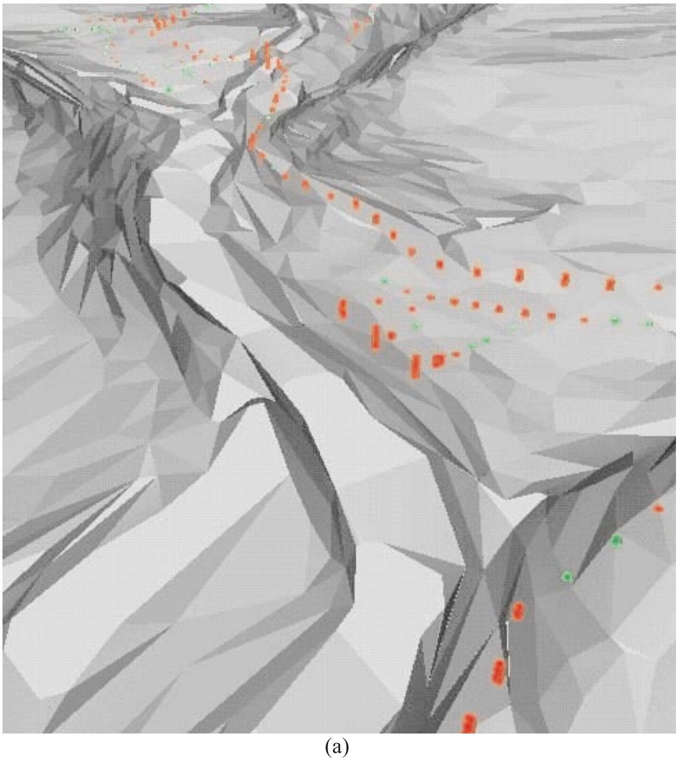
Figures 5a and 5b show the elevation errors present in parts of the study area. Both figures reveal that similar error values do cluster, exhibiting some degree of spatial autocorrelation. Although the statistical values represent an error measurement specific to the study area, it must be recognised that they are only estimates. The locations at which the points were measured are not necessarily representative of the entire area covered by the *Implicit TIN*. This is due to the majority of points being measured either in the valley towards the north of the study area (i.e. the observer locations), or else on the smoother hills towards the south (the surrounding terrain of the target location).

Table 2 represents the results of the probable visibility calculations of the 365 path profiles. As well as the multiscale representations, two Implicit TIN models were generated – a "bare-earth" TIN and the other with full topographic features. Two error models were generated for the stochastic simulation – the first defined using the OS definition of a RMSE of 1.0m and mean of zero, whilst the latter was defined using our observed RMSE of 1.6m and a mean of −0.9m. These error statistics were re-defined for the multiscale (generalised) versions of the TINs. The simulations were conducted 1000 times for each profile, whilst the categorisation of whether a profile is line-of-sight or not was made on the basis of whether the probable value exceeds a specific significance level. In Table 2, the first column represents the equivalent results from Table 1 for the number of correct interpretations made from multiscale "bare-earth" TINs with no topographic surface features modelled and no probable modelling. The second and third columns represent the probable visibility results for the "bare-earth" TINs using the error models derived from the OS estimates and our own survey findings. These are reported at the 50% and 99% significance levels (i.e. the profiles were classified as being LOS or not on the basis of the solutions for 500 and 990 or more perturbations of the data model profile out of 1000 trials). The last two columns represent the same experiment, but all the topographic surface features were considered in the TINs.

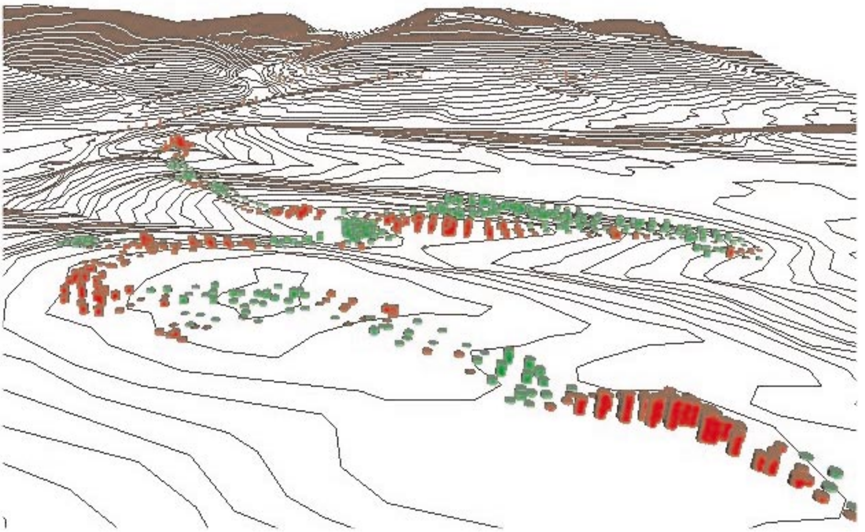
The effect of the different significance levels certainly has a bearing on these results and needs some explanation. In the first instance, greater confidence must be placed on

Table 2 Correlation between observed and probable visibility of 365 path profiles for a variety of Implicit TIN representations at multiple tolerances (1000 iterations)

Multiscale TIN	Bare TIN	OS Error Constrained Probable (Bare) TIN 50%/99% Sig.		Survey Error-Constrained Probable (Bare) TIN 50%/99% Sig.		OS Error Constrained Probable (Topographic) TIN 50%/99% Sig.		Survey Error-Constrained Probable (Topographic) TIN 50%/99% Sig.	
0m Tolerance	48.26%	53.17%	62.70%	52.78%	65.08%	92.46%	78.57%	90.87%	69.44%
2m Tolerance	47.88%	52.78%	61.11%	52.38%	63.49%	92.46%	82.94%	91.67%	75.79%
5m Tolerance	47.49%	51.98%	57.54%	51.98%	60.71%	92.86%	84.52%	92.86%	76.98%



(a)



(b)

Figure 5 Surveyed TIN elevation errors for the study area (Gilfach Goch in South Wales). Cylinders are proportional to the size of the error. Darker cylinders indicate negative errors and lighter cylinders positive errors (a) GPS versus TIN errors in the valley of Gilfach Goch (predominantly the viewing locations) (b) Electronic theodolite survey versus TIN errors in the gently rolling hills to the south of the region the results at the 99% significance level, as the effect of noise causing a mis-classification is almost eliminated. At the 50% level, there is a much higher chance of profiles being mis-classified. However, the behaviour of the TINs for the probable LOS analysis on the "bare-earth" and topographic surfaces is quite different at these two significance levels. For the "bare-earth" TINs, the results suggest that a probable visibility algorithm such as Fisher's (1991) can significantly improve the performance of the terrain models (from 48.26% to 65.08%). Furthermore, the results improve with a more accurate understanding of the errors in the original TIN (from 62.7% to 65.08%). Sparkes (2000) takes this analysis further by considering local errors in the TIN model, and prescribing an error distribution for the probable modelling based on the degree of slope of the triangles. Just as Figure 5 illustrates the correlation between elevation errors, Sparkes demonstrates the relationship between TIN error and triangle slope. As a profile is interpolated through the TIN, the slope of the current triangle is calculated and an error value is drawn from the distribution related to that slope value, which is then added to the interpolated elevation. If the interpolation is made across triangle edges, then the average of the two error values drawn from the two neighbouring triangles is taken. In this case, the probable LOS results are very similar to the improvements shown in Table 2. One drawback of Sparkes' approach is the need for a very large number of elevation samples in order to derive a range of error distributions corresponding to the different slope categories.

For the full topographic TIN models, the probable LOS modelling is poor, or certainly at the most significant levels in which we can place any confidence in the results. However, much better results are attained at the lower significance level of 50%. The performance of these results should be analysed in relation to the original results for the full topographic TINs (Table 1). As visibility can be determined correctly almost 93% of the time, then probable modelling will only degrade these results. The probable modelling of the "bare-earth" TINs will in effect perturb the surface sufficiently to simulate the addition of topographic features. For example, for the profiles that may have been blocked in the real world by buildings or vegetation, then there is a strong likelihood that the error model will supplement the TIN with noise that simulates these features. If the topographic features are represented accurately, the effect of probable modelling will be either to raise or lower these features and hence block or clear actual LOS or non-LOS profiles. At the 99% level this will be more significant, whereas at the 50% level the results mimic the "one-off" deterministic, precise computer model approach, i.e. the greater chance of mis-classification at the 50% level cancels out the effects of these errors. It is also worth noting that the generalised versions of the TINs perform worse for the "bare-earth" models, but perform better for the full topographic models. This is again due to the probable modelling compensating for the poorer performance of the generalised models.

In essence, probable modelling is a useful substitute for a lack of topographic features if it is beyond the means of the user to acquire such 3D data. In our field study, the probable modelling demonstrates the sensitivity of many of the visibility profiles and hence the viewshed to very small elevation errors. This is particularly true for determining visibility from within an urban or suburban environment, or one in which there is a lot of surrounding vegetation. If the 3D surface features have been accurately represented within the TIN then the effect of the error modelling will be to either remove some of these obstructions from the landscape, or to extrude further the heights of existing features. Either way, the effect of probable modelling on a complete digital surface model is of limited value, other than to determine the sensitivity of the viewshed.

7 Conclusions

The paper has considered the application of the *Multiscale Implicit TIN* to the problem of determining surface intervisibility. While the viewshed function has been a popular GIS tool over the last twenty years, we are hopeful that users will now question the performance of their analyses and the flexibility of their existing data models. In particular, there needs to be an increased realisation that visibility analysis is intrinsically flawed if users do not consider the effect of modelling topographic surface features. At the same time, the viewshed function is used by a variety of different users with different requirements of their analyses, be it large scale or small scale interpretation, precise or exploratory queries. A single scale data model cannot meet these requirements, whilst the main memory and processing demands of large scale digital surface models derived from products such as laser altimetry are beyond the means of even today's high specification personal computers. The *Multiscale Implicit TIN* provides a flexible framework for digital surface modelling that allows multiscale terrain models to be integrated with 3D topographic features. This has been demonstrated for the popular application of visibility analysis in which generalisation of the original contours has been shown not to degrade the overall performance of the intervisibility analysis. Generalisation of the lateral error in the TIN is perhaps not as critical as allowing constraints on the vertical error, such as with a Delaunay pyramid derived from a regular grid DEM.

For intervisibility analysis, the paper has attempted to quantify and qualify the performance of the Implicit TIN via a detailed field survey. This has shown that the influence of topographic features on the terrain surface will have the greatest impact on the performance of the digital terrain model. There is no substitute for good quality 3D topographic features. As such, it is important that developers consider how the current range of DTMs can be extended to incorporate 3D geometry. Currently, there are no commercial GIS that fully support the "correct" modelling of 3D features, other than for simple visualisation tasks. The *Implicit TIN* allows the user the choice of incorporating 3D features for functions such as intervisibility analysis, or the option to exclude them for functions such as hydrological modelling.

The results presented here are based on only one landscape, albeit a hilly landscape with the majority of viewing locations within some built-up areas. As such, we would not expect the results to be completely indicative of what all users would experience with their own choice of digital terrain models and landscapes. For more rural landscapes, or where the observer locations are in less built-up areas, we would expect much better performances and a smaller differential between our particular scenarios. For more urban landscapes, we would expect the differential to widen as the effect of the topographic features becomes more critical. Needless to say, more validation studies are required to identify the problems of digital surface modelling and to raise the awareness of the error in visibility analysis if topographic features are not fully considered.

The paper has also demonstrated the feasibility of probable intervisibility modelling applied to TINs. Most developers who have addressed the probable viewshed problem have developed solutions applied to regular grid DEMs, generally without topographic features. The approaches and algorithms are equally valid for TINs. The results have shown that probable visibility modelling is only of benefit for digital terrain models bereft of its topographic features. In these cases, actual LOS prediction has been shown to increase by up to 17% as the error model simulates the presence of topographic features, i.e. the probable solution will be significantly better than the absolute solution offered by a single DTM representation. An understanding of the specific error in any DTM will be of benefit in producing better estimates of probable visibility. For terrain models with accurate 3D topographic features, probable visibility modelling does not offer any improvements over the traditional absolute approach. However, probable modelling demonstrates the sensitivity of many LOS profiles to very small elevation (terrain and topographic) errors.

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